Action-Free Reasoning for Policy Generalization

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***Abstract*—End-to-end imitation learning offers a promising approach for training robot policies. However, generalizing to new settings—such as unseen scenes, tasks, and object instances—remains a significant challenge. Although large-scale robot demonstration datasets have shown potential for inducing generalization, they are resource-intensive to scale. In contrast, human video data is abundant and diverse, presenting an attractive alternative. Yet, these human-video datasets lack action labels, complicating their use in imitation learning. Existing methods attempt to extract grounded action representations (e.g., hand poses), but resulting policies struggle to bridge the embodiment gap between human and robot actions. We propose an alternative approach: leveraging language-based reasoning from human videos - essential for guiding robot actions - to train generalizable robot policies. Building on recent advances in reasoning-based policy architectures, we introduce Reasoning through Action-free Data (RAD). RAD learns from both robot demonstration data (with reasoning and action labels) and action-free human video data (with only reasoning labels). The robot data teaches the model to map reasoning to low-level actions, while the action-free data enhances reasoning capabilities. Additionally, we will release a new dataset of 3,377 human-hand demonstrations compatible with the Bridge V2 benchmark. This dataset includes chain-of-thought reasoning annotations and hand-tracking data to help facilitate future work on reasoning-driven robot learning. Our experiments demonstrate that RAD enables effective transfer across the embodiment gap, allowing robots to perform tasks seen only in action-free data. Furthermore, scaling up action-free reasoning data significantly improves policy performance and generalization to novel tasks. These results highlight the promise of reasoning-driven learning from action-free datasets for advancing generalizable robot control. Website: here.**

I. INTRODUCTION

Training visuomotor policies via imitation learning is an appealing paradigm for robot control. However, an outstanding challenge for current end-to-end learning methods is to generalize to new settings beyond their training data, such as new scenes, new task instructions, and new object instances.

While there are promising signs of scaling up datasets being the solution, we simply have not reached the scale needed for comprehensive generalization, and one might argue that collecting data at such scale is practically infeasible (1; 2; 3; 4).

On the other hand, many see tapping into human video datasets, consisting of humans directly performing tasks as opposed to collecting robot data, as the answer (5; 6; 7). This data is cheap to collect and already present at scale in Internet datasets. However, human videos lack action labels, making supervised learning methods like imitation learning very difficult. Some works tackle this challenge by extracting *grounded action-like* representations from video as labels for imitation learning, for example hand poses or object affordances (8; 9; 10; 11). However, extracting grounded actions from human videos often makes assumptions about the scene and the embodiment gap (e.g., how the hand pose maps to the robot action or relying on paired human and robot data) which can limit their usefulness in practice.

Instead of extracting grounded actions from videos and the restrictive assumptions that come with it, we ask: *is there any other behavioral information – that still directly influences robot actions – that we can extract from human videos, and more generally action-free data?* Our insight is that human videos contain vast amounts of *higher-level reasoning* that guide robot action prediction, and this reasoning information can be captured via language.

We introduce our method, Reasoning through Action-free Data (RAD), a robot policy that leverages reasoning traces extracted from action-free data. RAD trains a large transformer model on a mixture of robot demonstration data with both reasoning and robot action labels, and action-free (human video) data labeled with *just* reasoning. The robot data teaches the model to autoregressively go from reasoning to low-level actions, while the action-free data augments the reasoning knowledge, thus boosting the reasoning capabilities of the model. We label reasoning traces by leveraging pretrained vision-language models such as Gemini with hindsight knowledge as done in prior work (12).

We experimentally validate that learning from action-free reasoning data transfers well across the embodiment gap – showing 20% better performance on tasks only seen in the action-free data over models not finetuned with RAD. Additionally, we demonstrate that having larger amounts of action-free reasoning data improves the capacity of the model to generalize in language space to completely unseen tasks with RAD outperforming baselines by 15% on generalization tasks (that have never been seen in robot or human data).

II. RELATED WORK

Recent works have explored the use of pre-trained Vision-Language Models (VLMs) as backbones for Vision-Language Action Models (VLAs) which directly predict low-level robot actions. For example, RT-2-X (2) fine-tunes the 55B-parameter PaLI-X VLM (13) on the Open-X Embodiment dataset (2), and OpenVLA (3) uses a 7B-parameter Llama 2 LLM backbone with a vision encoder based on DINOv2 (14) and SigLIP (15). The promise of VLAs for manipulation is to build off of generalization of VLMs which have been trained on Internet-scale vision-language data. More recently, several works have studied the role of more fine-grained language such as "language motions" as intermediate representations to predict (16) or explicitly performing multiple steps of reasoning over language as well as other visually-grounded features such as bounding boxes as a way of guiding large pretrained policies (12).

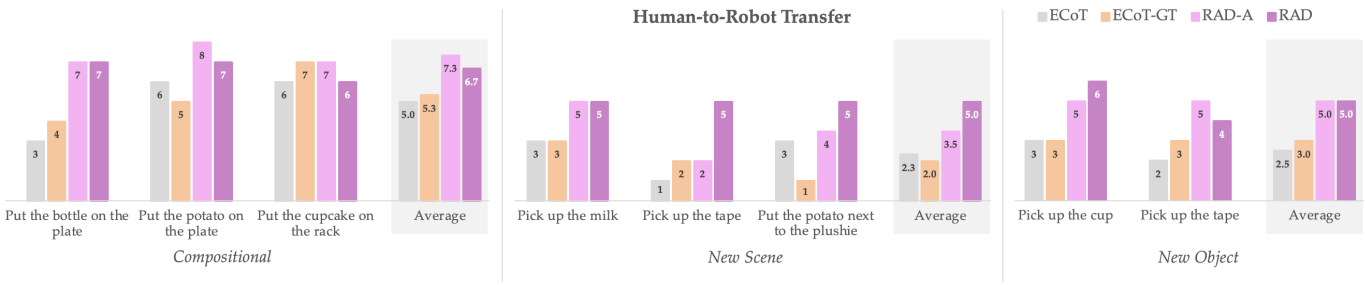

Fig. 1: RAD outperforms baselines where human video data was trained on, but no new robot data was provided. RAD-A is RAD trained only on human video data for the given axis of generalization. ECoT-GT is finetuned on the same data as RAD, but only using human hand locations (and not the full reasoning data).

A large number of prior works in imitation learning for robotics focus on learning from demonstrations collected via teleoperation by expert operators. This method of collecting data is costly, so a number of prior works have investigated ways to leverage existing data sources of human videos to improve robot policy learning — for example, by pre-training visual representations (17; 18; 19), learning reward functions (20; 21; 22). Several works learn priors from human video datasets and/or in-domain human videos (23; 24; 6; 10) or aligning paired/unpaired examples of human videos and robot demonstration videos (25; 26; 27; 28) or simulations (29). These works are still fundamentally limited by the quantity of robot demonstrations. Another line of work leverages intermediate representations for predicting robot actions downstream, but make assumptions about the human hand behavior, which is not necessarily the same as the robot (30; 8). Our work goes beyond existing methods that rely on generating intermediate representations for action predictions by generating detailed reasoning steps about human video demonstrations.

III. Method

In this section, we will describe our problem setting and lay out our assumptions. As an overview, RAD involves two major steps. First, annotate action-free data with language reasoning (**??**). Second, train a reasoning-based policy on a combination of robot demonstration data with both actions and reasoning chains and action-free data with only reasoning chains (**??**).

In multi-task imitation learning, we are given a dataset $\mathcal{D} = \{(o_1, a_1, g_1), \dots (o_N, a_N, g_N)\}$ consisting of tuples of observations $o \in \mathcal{O}$, actions $a \in \mathcal{A}$, and task specifications $g \in \mathcal{G}$ which are often formulated in language. The objective is to learn the expert action distribution $P(a \mid o, g)$ conditioned on an observation o and a task specification g.

We now define the objective of *reasoning-based* multi-task imitation learning. We assume there exists some chain of C steps of intermediate language reasoning that links an observation o and action label a, which we denote as $(l^1, \dots, l^C)$. We discuss how these reasoning chains are generated in **??**. The distribution of each reasoning step l^j only depends on the preceding reasoning steps $(l^1, \dots, l^{j-1})$ as well as o and g. The distribution of actions a depends on all reasoning steps $(l^1, \dots, l^C)$ and the observation o and task g. We define the objective of the reasoning-based multi-task imitation learning problem as learning the expert joint reasoning and action distribution $P(a, l^1, \dots, l^C \mid o, g)$. In this setting, each (o_i, a_i, g_i) tuple in $\mathcal{D}$ is augmented with a reasoning chain $(l_i^1, \dots, l_i^C)$. We wish to learn a distribution P_θ parameterized by θ that maximizes the log-likelihood of the reasoning and action data in $\mathcal{D}$:

$$
\begin{aligned}
L(\theta) &= \sum_i^N \log P_\theta(a_i, l_i^1 \dots l_i^C \mid o_i, g_i) \\
&= \sum_i^N \log P_\theta(a_i \mid l_i^1 \dots l_i^C, o_i, g_i) \prod_j^C P_\theta(l_i^j \mid l_i^1 \dots l_i^{j-1}, o_i, g_i) \\
&= \sum_i^N \log P_\theta(a_i \mid l_i^1 \dots l_i^C, o_i, g_i) \\
&\quad + \sum_i^N \sum_j^C \log P_\theta(l_i^j \mid l_i^1 \dots l_i^{j-1}, o_i, g_i) \\
&= L_{\texttt{action}}(\theta) + L_{\texttt{reasoning}}(\theta)
\end{aligned}
$$

Our key insight in RAD is that *action-free* datasets—such as human video data, which is often easier to collect than robot demonstrations—can provide additional supervision for the joint action-reasoning distribution P_θ which can in turn aid generalization. Specifically, we assume access to some action-free data $\tilde{\mathcal{D}}$ consisting of M samples of $(\tilde{o_i}, \tilde{g_i}, \tilde{l_i}^1 \cdots \tilde{l_i}^{C_i})$. Here, sample i includes the first $C_i \geq 1$ steps of language reasoning, where C_i can vary between samples. For example, we might have varying levels of confidence in our full reasoning labeling pipeline for different subsets of our action-free data – some samples might only be confident in the higher level reasoning steps (lower C_i) for example due to a large embodiment gap, while others might have high quality lower level reasoning (higher C_i). Importantly, this flexibility of reasoning labeling could enable our framework to incorporate vast scales of varying quality and embodiment reasoning data to improve *each step* of the reasoning process independently from action prediction.

In this work, we optimize the objective above along with an auxiliary objective $\tilde{L}_{\texttt{reasoning}}(\theta)$ for the action-free data,

defined similarly as follows:

$$\tilde{L}_{\texttt{reasoning}}(\theta) = \sum_{i}^{M} \sum_{j}^{C_i} \log P_\theta(\tilde{l}_i^{\,j} \mid \tilde{l}_i^{\,1} \ldots \tilde{l}_i^{\,j-1}, \tilde{o}_i, \tilde{g}_i)$$

Note that since sample i contains the first C_i reasoning steps, we have enough information to model each of the C_i reasoning steps conditioned on previous reasoning steps and the current observation and task.

IV. Experiments

In this section, we evaluate how RAD enables transfer from human videos to robot policies and generalization beyond settings in the human videos or robot demonstration data. Specifically, we seek to answer the following questions:

Q1 – Human-to-Robot Transfer: Can RAD enable learning new tasks seen only in the human video data and not the robot demonstration data?
Q2 – Reasoning Generalization: Does reasoning in RAD enable generalization to novel tasks beyond both the robot demonstration data and human video data it was trained on?
Q3 – Cross-Environment Transfer: Can RAD learn new tasks from human video data in out-of-domain environments?

A. Evaluating Generalization

Generalization Tasks: We evaluate RAD across a variety of generalization tasks. These tasks comprise three main axes of generalization:

1) **Compositional Generalization**: In this axis, the objects, tasks, and scenes are all seen in pre-training data (Bridge V2 data), but not in those particular configurations. For example, pizza and salt both exist in Bridge V2, but salt is never placed on the pizza.
2) **New Object Generalization**: This axis introduces unseen objects for known behaviors (e.g., *pick cup* $\rightarrow$ *pick plushie*).
3) **New Scene Generalization**: This axis requires generalizing to novel backgrounds and distractor objects for seen tasks; for example, picking up a known object with a pot in the background.

Note that the Compositional Generalization axis tests the model's ability to *interpolate* the training data, while New Object and New Scene axes test the model's ability to *extrapolate* from the training data. Exact tasks for each axis can be found in Section V-F.

Methods: To test the efficacy of reasoning in learning from human video data, we evaluate the following models in our generalization scenarios.

1) **Embodied Chain-of-Thought (ECoT)** (12) A state-of-the-art action reasoning model trained on Bridge V2, but without any human video data.
2) **ECoT w/ Gripper Tracking (ECoT-GT):** ECoT finetuned on the same human video data as RAD, but only generates the `GripperPosition` portion of the reasoning chain. This is analogous to how prior work learns from extracted pose information only in human videos, but does not extract higher level language reasoning (30; 10; 9).
3) **RAD (Ours):** ECoT finetuned on the full chain of reasonings generated from human video data.
4) **RAD-A (Ours):** Same as RAD, but trained on only human videos from one axis of generalization at a time (the axes are described in Section IV-A).

B. Can RAD enable transfer from human-to-robot embodiments?

First, we assess if RAD can learn accurate reasonings and robot actions on new tasks that are present only in human video demonstrations. We train the axis-specific models (RAD-A) only on human video data for that axis (8-12 tasks with a total of 320-500 videos per axis). We evaluate these axis-specific models against zero-shot ECoT, as well as RAD (trained on human video data from all three axes) and ECoT-GT models trained on our full human video dataset.

In Fig. 1, we find that despite having no new robot demonstration data for these new tasks, RAD-A achieves consistently higher success rates than zero-shot ECoT and ECoT-GT across all areas of generalization (**Q1**).

Compositional: On compositionally new tasks, RAD-A outperforms ECoT by 23% and ECoT-GT by 20%. RAD outperforms ECoT and ECoT-GT by 17% and 13% respectively. Qualitatively, RAD models demonstrates significantly better reasoning capability, particularly in the second step of pick place tasks (such as placing the object of interest in the desired location).

New Object: On tasks with new objects, RAD and RAD-A both improves on ECoT and ECoT-GT by 25% and 20%, respectively. RAD models demonstrate substantially better ability to reason about grasp points on new objects, such as moving towards the sides of large cups instead of the middle.

New Scene: RAD models also substantially outperform baselines on novel scenes (containing distractors and other scene modifications). RAD-A outperforms ECoT by 12% and ECoT-GT by 15%. The full RAD model had stronger performance, outperforming ECoT by 27% and ECoT-GT by 30% - potentially due to improves ability to ignore distractors from the larger dataset it was trained on. Reasoning traces on RAD models also appeared to be more accurate, with ECoT often becoming distracted and generating non-sensical reasonings. These results indicate that augmenting chain-of-thought models with reasoning from human video data improves these models' ability to reason about and infer robot actions on previously unseen task configurations.

C. Can RAD train more generalizable policies?

Ultimately, training on large datasets of human video data should enable VLAs to generalize not only to human demonstrated tasks, but also to completely unseen scenarios. To explore if RAD enables training more general models, we evaluate our model against ECoT on 10 novel tasks (unseen in

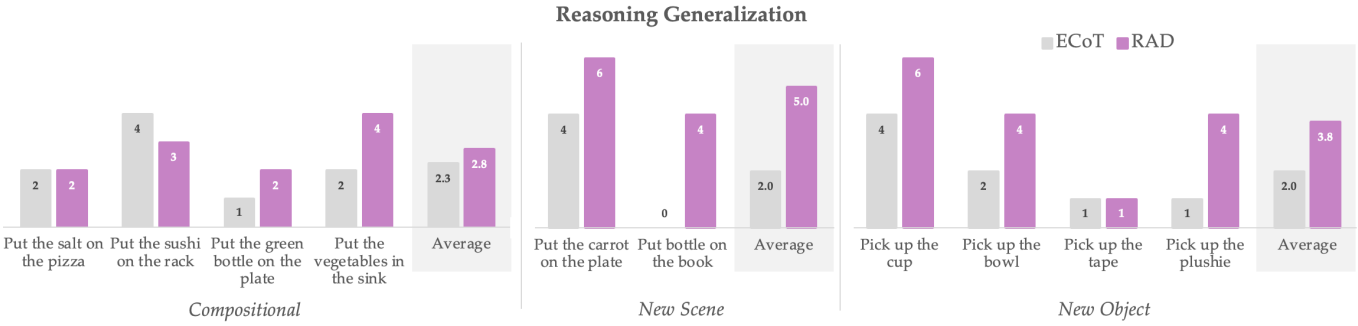

Fig. 2: RAD compared to ECoT for tasks contained in neither human or robot data. RAD shows improved performance across all three axes of generalization.

both human and robot data) comprising all three generalization axes. Results are presented in Fig. 2.

Compositional: On compositionally novel tasks, RAD outperforms ECoT by 5%. RAD reasoned better than ECoT over multi-step tasks, such as knowing where to place the salt after picking it up.

New Object: RAD substantially improves performance on tasks with unseen objects, such as bowls and large cups, despite not seeing such objects in human or robot training data. RAD achieves 30% higher success compared to ECoT.

New Scene: In novel scenes (environments with large distractors in the scene, such as cloth, pots, and a large plushie), RAD reached 18% higher success rate than ECoT. Qualitatively, ECoT struggled to reason about the new scene and would often generate poor reasonings and execute seemingly random actions, whereas RAD generated correct reasoning which informed downstream action prediction.

This indicates that reasoning in RAD enables better generalization to a variety of unseen tasks, without training on any new human or robot data (**Q2**).

D. Can RAD leverage data from new environments?

To truly leverage large-scale video data, generalist robot policies must learn from demonstrations in diverse scenes. Thus, we first train RAD with human video data in unseen environments to see how well it can incorporate this data, and then we compare its performance to RAD trained on in-distribution human video data (i.e., same environment for both human video and robot evaluation).

Human Videos from New Environment: We seek to understand how RAD responds to human video data collected outside the Bridge V2 environment. We first collect data for two unseen tasks in a new tabletop setup (unseen in Bridge V2 data). Then, we evaluate models trained on this new enviroment data in the original Bridge Toy Sink environment. In Table I, we see that models trained on this data outperform ECoT by 16% and ECoT-GT by 13%. Similarly to Section IV-B and Section IV-C RAD models showed significantly better ability to reason about grasp points, such as where to pick up the controller, despite the data being in a different environment (**Q3**).

In-distribution vs. Out-of-Distribution Human Data: Next, we assess how RAD performance scales with increased data for the same tasks collected in-distribution (in the miniature Toy Sink setup) versus out-of-distribution (various real world kitchen and office environments). To do so, we collected 100 additional demos for the *pick up the tape* task in the Toy Sink setup. We also collected 250 out-of-domain demos for *pick up the tape* in novel environments such as real kitchens, countertops, and desks. Then, we trained RAD on two different data mixtures:

1) The original RAD data mix (which already had 40 "Pick up the tape" demos) + in-distribution data and
2) The original RAD data mix + out-of-domain data.

Results for both mixtures are shown in Table II. We find that RAD models trained on both in-domain (+30% success) and out-of-domain data (+25% success) show improved performance over the original model (**Q3**). Qualitatively, RAD models were better able to reason about when to bring the gripper to the level of the tape, with ECoT models often moving to low and knocking over the tape, which is abnormally tall with respect to objects in Bridge V2.

V. Discussion

In this work we present RAD, a new way to train generalist robot policies from human video data. RAD learns to predict *reasoning*, which can be labeled on both robot and human video data. We find that RAD enables VLAs to cross the embodiment gap, and to learn tasks represented in only human video data. Models trained with RAD are also able to generalize to completely unseen tasks (not present in either robot or human data). Finally, we find RAD responds positively to data from out-of-domain environments, enabling models to learn new tasks from environments completely separate from the target domain. These results demonstrate that RAD is a promising step towards training generalist robot policies, laying the groundwork for models that can leverage both robot data and large-scale human video data.

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APPENDIX

We outline the dataset collection and reasoning generation procedure in Section V-A, Section V-B, Section V-C, and Section V-D. The models, training procedure, and baselines are described in detail in Section V-E. Finally, Section V-F provides examples of results and description of reported success rates.

A. Reasoning Steps in RAD

While our setup can in principle work with different formulations of language reasoning steps, we instantiate our algorithm with the following reasoning steps from prior work (12):

- `TaskPlan` (l^1): describes a list of subtasks to achieve g.
- `SubtaskReasoning` (l^2): reasons about which subtask currently needs to be executed in the plan.
- `Subtask` (l^3): predicts the subtask that currently needs to be executed.
- `MoveReasoning` (l^4): reasons about the motion needed to achieve the subtask in the scene.
- `MovePrimitive` (l^5): predicts a movement primitive in language.
- `GripperPosition` (l^6): predicts the pixel position of the end-effector.
- `VisibleObjects` (l^7): predicts the bounding box coordinates of objects in the scene.
- `Action` (a): predicts the low-level robot action as an end-effector position delta.

We note that these reasoning steps trace through information at an increasing amount of physical and spatial groundedness—beginning with high-level scene reasoning over tasks and subtasks, transitioning to reasoning over language motions, followed by spatial information about the gripper and objects, and concluding with the low-level robot action. We take advantage of this fact in designing a pipeline to label reasoning in action-free data, as we describe in the following section.

B. Labeling Reasoning in Action-free Data

In order to construct $\tilde{D}$—our dataset of observations, goals and action-free reasoning—we need to generate labels for the reasoning steps above from human videos. Our pipeline is similar to the automated procedure used by Embodied Chain-of-Thought (ECoT) (12) for generating reasoning over robot demonstrations, with some key modifications to handle human videos. To obtain reasoning labels for robot demonstrations, ECoT first generates `GripperPositions` and `VisibleObjects` tags using off-the-shelf object detectors to obtain bounding boxes. Then, it extracts `MovePrimitive` (e.g. "move to the left") directly from actions using an automated heuristic. Conditioned on these more grounded reasoning steps (l^5, l^6, l^7) and the image observation o, it queries Gemini (31) to label the prior reasoning steps, from `TaskPlan` through `MoveReasoning` $(l^1, \ldots, l^4)$.

In the action-free setting with human videos, we note that we can still extract high-level reasoning with Gemini, as well as extract `VisibleObjects` with off-the-shelf object detectors. However, generating the more action-grounded reasoning steps is challenging: we can no longer extract `MovePrimitives` or `GripperPositions` automatically because we lack explicit action labels. In order to overcome this, we extract the `MovePrimitives` and `GripperPositions` using HaMeR (32), a hand keypoint and pose tracking method. Given these predictions, we can extract the `MovePrimitives` from changes in the hand pose information: first, we study each axis of the change in hand poses for each frame; then, we label the move primitive based on the dominant axis of motion. We find that this works reliably for tracking gripper and positional movement primitives, but is not as reliable for detecting rotational movement primitives. We outline this labeling procedure in Fig. 3.

C. Training on Partial Reasoning Chains

To train on mixtures of demonstration and action-free data, we use the ECoT and OpenVLA (12; 3) architecture, which trains a pre-trained VLM transformer with 7B parameters to predict sequences of language reasoning and then action tokens. This model is pretrained on Internet-scale vision-language tasks, such as bounding box detection or object localization. Thus, it benefits from a strong vision and language priors. With ECoT and OpenVLA, it is then further trained on robot demonstration data, and in the case of ECoT, predicts language reasoning tokens prior to action tokens. In RAD, we reuse this paradigm for the robot demonstration data, but for the new action-free data, our "labels" for training contain only reasoning as described in Section V-B.

D. Dataset Details

Data Collection: Our main human video data collection was on the Bridge V2 Toy Sink setup. We aligned one camera based on the original Bridge V2 scene. We also set up a second camera from directly behind the WidowX gripper to better track hand movement as seen in Fig. 4. Example tasks are shown in Fig. 5. We used HaMeR to track the hand using the secondary camera perspective. We used the average location of the thumb tip and index finger tip points tracked by HaMeR as the gripper location. Based on the delta gripper position between frames, we characterized every frame as "stop", "move forward", "move backward", "move left", "move right", "move up", or "move down" movement primitives. We used the average distance between the thumb tip and index tip to determine "close gripper" and "open gripper" primitives. For reasoning generation on the human videos, we followed the the pipeline of (12), but used this HaMeR tracking in place of proprioception and SAM to generate movement primitives and gripper locations.

Data Mixtures: For RAD-A models in Section IV-B we collected 392 demonstrations for the compositional generalization dataset, 304 demonstrations for the new object dataset, and 280 demonstrations for the new scene dataset. The full RAD model as well as ECoT-GT model were both trained on all three of

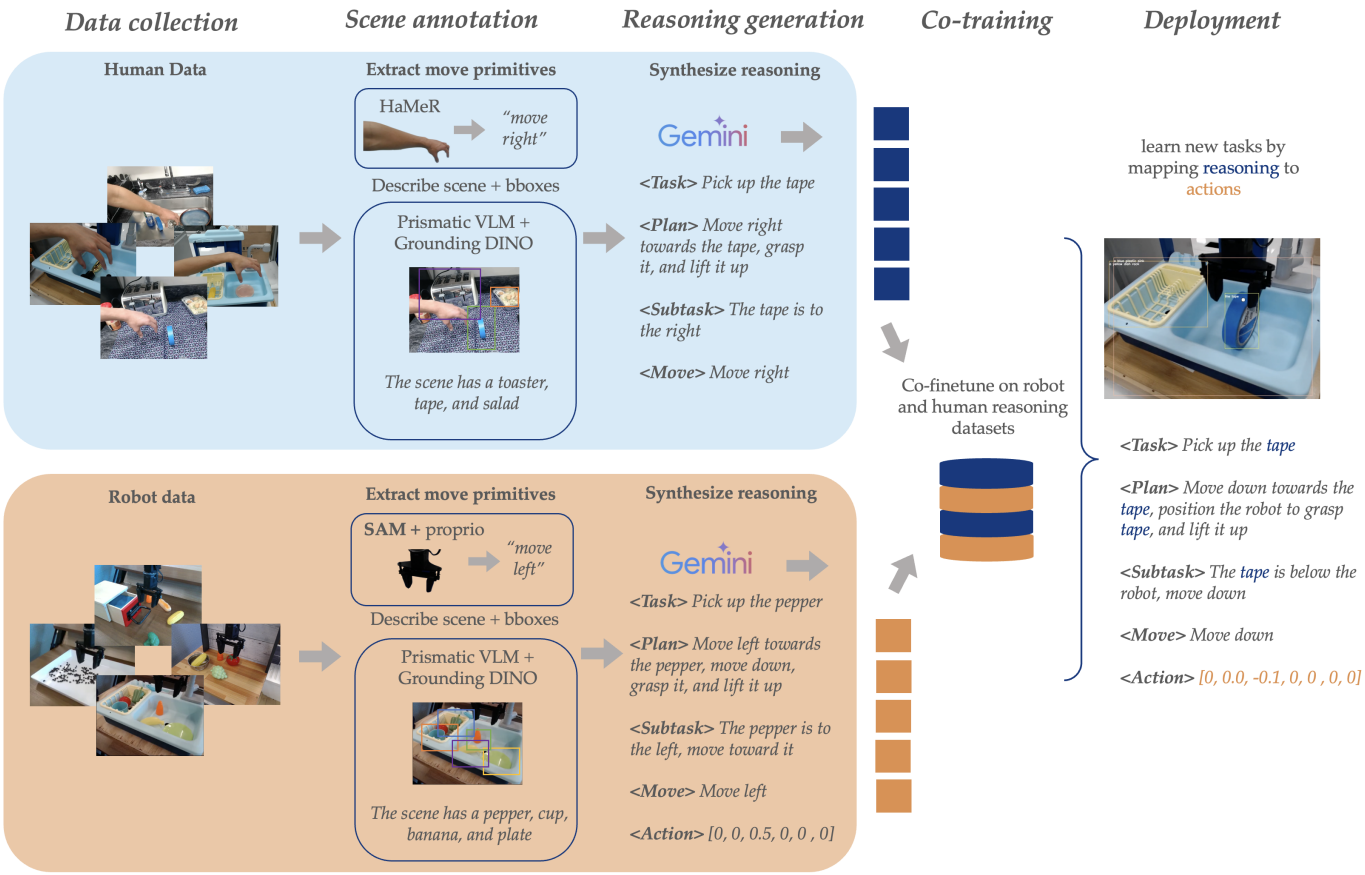


Fig. 3: RAD generates reasonings on both human and robot data using a suite of pretrained models. Scene descriptors and object bounding boxes for both human and robot data are generated using Prismatic VLM and Grounding DINO. While SAM and proprioception can be used to generate movement primitives for robot data, RAD relies on HaMeR to track human hand data for primitive generation. For both data types, the scene descriptions, bounding boxes, and movement primitives (as well as actions for robot data) are synthesized by Gemini into reasoning data in natural language. These reasonings are tokenized and fed into a mixed dataset containing both human and robot data for co-finetuning.

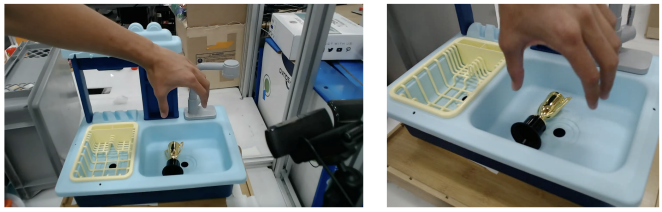


Fig. 4: The main Bridge V2 perspective (right) versus the secondary perspective used for hand tracking (left).

these datasets as well as 640 additional demos to make 1616 total demonstrations.

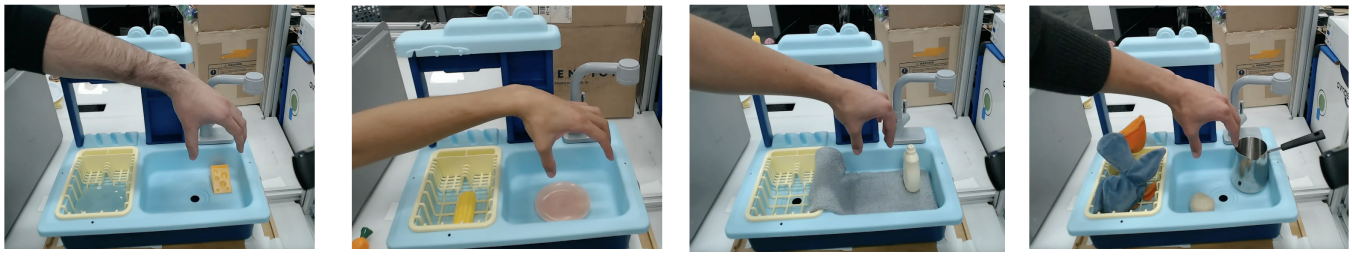
Data for Table I was collected from two new tabletop environments as shown in Fig. 6. Each task in Table I had 40 total demos collected. For Table II we collected 100 additional demos in the Toy Sink setup for the "in-distribution" evaluation. For the "OOD" data, we collected 50 demos from 5 different scenes as show in Fig. 7.

E. Training Details

RAD uses the Prismatic VLM [35] architecture from OpenVLA (3), which fuses pre-trained SigLIP (15) and/or DinoV2 (14) features for the visual encoder, and a LLaMA 2 7B (33) language backbone. All models are fine-tuned to convergence with a learning rate of 2e-4, a LoRA batch size of 2, and anywhere from 2 to 8 GPUs (L40s or A40). Training of the ECoT-GT baseline is the same as RAD except the loss term for the stop token is omitted and we also adjust the query prompt from "What action should the robot take to [*task*]?" to "Where is the robot hand in the image?".

F. Results

Real-World Environments: We use a 6-DoF WidowX robot arm for our experiments. We perform all evaluations in Section IV-B and Section IV-C on the Toy Sink setup from (34), to ensure fair comparison with existing pre-trained models. All human video data for Section IV-B and Section IV-C was also collected in the Toy Sink setup (1616 demonstration videos), using both the standard Bridge V2 camera setup, as well as



Put the cheese on the plate *Put the corn on the plate* *Put the bottle on the rack* *Put the potato on the plushie*

Fig. 5: Example human video tasks collected.

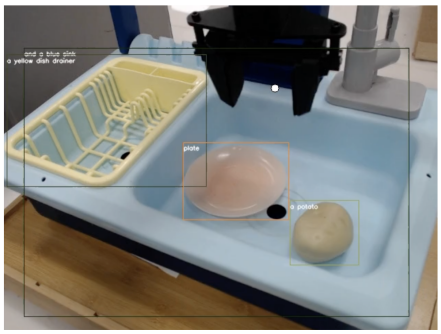
Pick up the tiger *Put the sushi on the book* *Pick up the controller*

Fig. 6: Task demonstrations collected in environments outside of Bridge V2 to assess how RAD responds to data from different types of scenes.

Fig. 7: Real world environment data RAD is trained with for Section IV-D.

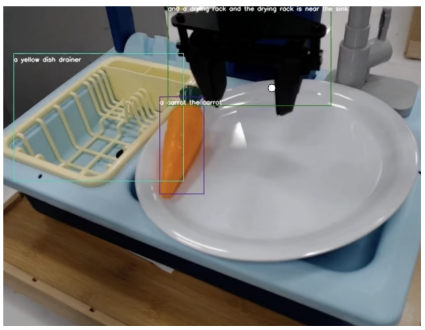
an additional camera for better hand tracking. Notably, the Bridge V2 setup is comprised of mostly miniature toy replicas of real world objects such as small kitchen supplies, blocks, and home supplies. Therefore, we also seek to assess how RAD responds to data from real-world human environments, and learns to interact with realistically sized objects. We thus collect data in two additional environments: a plain tabletop and a cluttered desk, as well as various real home and kitchen environments. This data was used to assess how RAD responds to data from unstructured environments in Section IV-D.

Evaluation Criteria: Every task was evaluated 10 times. Objects were randomly placed throughout the scenes in a different spot for all 10 trials. For pick and place tasks, partial credit (0.5) was given for successfully picking up the object, but placing in the wrong location. For pick objects, no partial credit was given except for the "pick up the controller" task, which had an exceptionally high payload. Thus partial credit was given for grasping the object, even if the object slipped out of grasp upon being lifted.

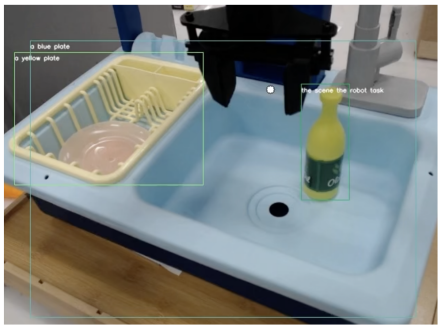


Put the potato on the plate

Pick up the cup



Put the carrot on the rack



Put the bottle on the plate

Pick up the plushie

Put the bottle on the book

Fig. 8: Example tasks for compositionally new tasks (left), new objects (middle), and new scenes (right).

TABLE I: Cross-Environment Transfer

Task	**Model**	**Success Rate**
pick up the cup	ECoT	3/10
	RAD	6/10
	ECoT-GT	4/10
put the sushi on the book	ECoT	4.5/10
	RAD	6.5/10
	ECoT-GT	5/10
pick up the tiger	ECoT	3/10
	RAD	3/10
	ECoT-GT	3/10
pick up the controller	ECoT	2/10
	RAD	3.5/10
	ECoT-GT	2/10

TABLE II: Data Scaling

Data	**Model**	**Success Rate**
Original model (40 demos)	ECoT	2/10
	ECoT-GT	3/10
	RAD	4/10
	RAD-A	5/10
Same Environment (+100 ID demos)	RAD	7/10
	ECoT-GT	4/10
New Environments (+250 OOD demos)	RAD	6.5/10
	ECoT-GT	5/10